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Research Article

Vehicle routing problem with cross-docking in a sustainable supply chain for perishable products

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Abstract

Today's transportation systems, which largely rely on the combustion of fossil fuels, play a significant role in contributing to energy-related greenhouse gas (GHG) emissions, thereby raising serious concerns about sustainability. As awareness of environmental issues grows, incorporating sustainable practices into logistics, particularly in cross-dock scheduling, is becoming increasingly vital. This paper introduces a sustainable vehicle routing problem (VRP) that integrates cross-docking to enhance decision-making within logistics systems. Beyond purely economic considerations, it emphasizes critical aspects like environmental impacts, notably CO_2 emissions, and social factors such as equity among drivers and overall customer satisfaction. To tackle these complex challenges, a metaheuristic approach blending Genetic Algorithms (GA) with mixed integer programming (MIP) is proposed as an effective solution strategy. The method's efficacy is validated through various instances of differing sizes, revealing that the GA yields results with minimal deviation from optimal fitness values in smaller instances. Additionally, a comprehensive real case study is conducted to showcase the model's applicability in practical scenarios and finally, some suggestions for further researches are given. This study not only illustrates the operational benefits of the proposed approach but also underscores the importance of sustainable logistics in mitigating environmental impacts while fostering social equity and enhancing customer experience.

Keywords: Sustainable vehicle routing problem; Cross-docking, Freshness; Job satisfaction; Genetic algorithm; Social responsibility

1. Introduction

A cross-docking strategy allows logistics companies to decrease the delivery time and cost of storage. At receiving doors of a cross-dock facility, products are unloaded from incoming vehicles carrying products from suppliers, sorted and staged in accordance with customer orders, and then loaded onto outgoing vehicles to be delivered to customers (Chargui, Bekrar, Reghioui, & Trentesaux, 2020). Typically, products do not spend more than 24 hours in a cross-dock facility (Arbabi, Nasiri, & Bozorgi-Amiri, 2021). It is recommended to combine cross-dock scheduling with the routing of outgoing vehicles in a vehicle routing problem with cross-docking (VRPCD) in order to achieve an optimized delivery. For a comprehensive review of VRPCD papers, see Nasiri, Rahbari, Werner, and Karimi (2018).

The IPCC's fifth assessment report states that, to limit warming to below 2 degrees Celsius, GHG emissions need to reduce by 40 to 70 percent from 2010 levels by 2050 (IPCC, 2014). As a result, governments are under increasing pressure to enact legislation to reduce the volume of these emissions (Benjaafar, Li, & Daskin, 2012). One of the major drivers of GHG emissions has been identified as logistics and supply chain operations.

In the past, the primary objectives of cross-docking facility managers were to minimize costs or maximize profits. However, at present, these managers also have a responsibility to consider other aspects of sustainable development, such as the environmental and social aspects. Brundland (1987) Described sustainability as: “the ability to meet the needs of the present without compromising the ability of future generations to meet their own needs”. In the next two subsections, we investigate the works related to VRPCD, and consider sustainability, or at least the environmental aspect.

Reducing food waste has a significant impact on feeding hungry people around the world. The supply chain can be designed in a way that reduces waste. Rahbari et al. (2019) presented a bi-objective model for VRP with cross-docking for perishable products while tackling uncertainties related to outbound vehicle travel time and product freshness-life.. A new multi-objective model was utilized by Shahabi-Shahmiri et al. (2021) to schedule and route a fleet of heterogeneous vehicles carrying perishable products through multiple cross-docking systems. Theophilus et al. (2021) for the first time developed a new mixed-integer model at a cold-chain cross-docking terminal for

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scheduling trucks to improve perishable product distribution efficiency. In this study, a vehicle routing problem with cross-docking in a sustainable supply chain is investigated for perishable products, which can reduce the amount of waste.

1.1. Sustainable cross-docking

Cross-docking is a logistics practice that enhances sustainability across supply chains by reducing waste and optimizing resource use. Environmentally, it lowers transportation emissions by minimizing transit time and distance, optimizes space usage, and reduces waste, particularly for perishable goods. Economically, cross-docking improves cost efficiency by lowering inventory holding and warehousing fees, streamlining operations, and enhancing reliability, which can boost customer satisfaction and brand loyalty. Socially, it can contribute to job creation within logistics and supply chain management, foster community engagement through environmentally friendly practices, and improve workplace health and safety by reducing handling times. Overall, cross-docking presents a comprehensive approach to promoting sustainability in supply chain management.

There are few sustainable and green studies in this scope. Yin, Lyu, and Chuang (2016) investigated green VRPCD considering constraints on the amount of CO2 emissions. Yin and Chuang (2016) tried to reach an efficient fuel consumption through cost minimization and CO2 emissions in a vehicle routing problem in which the vehicles transport the products through a cross-dock. Govindan, Jafarian, and Nourbakhsh (2015) considered sustainable order allocation and sustainable supply chain through two objectives. The first objective minimizes related costs and the second objective minimizes the environmental impact of all the members of a supply chain and established plants, distribution centers, and cross-docks are taken into account. Abad, Vahdani, Sharifi, and Etebari (2018) studied a pollution-routing problem(PRP) with a cross-docking system. In order to solve this problem, they presented a multi-objective mathematical model and used three metaheuristic algorithms. Santos, Martins, Amorim, and Almada-Lobo (2021) considered economic and environmental issues as a collaborative problem between a leading retailer (LR), a third party logistics provider (3PL) and different producers. To reduce the emissions and pollution, Tabatabaei, Safi, and Shafiei Nikabadi (2021) proposed a mathematical model to schedule transportation and routing and cross-docking. They used NSGAII to solve the proposed model.

Rezaei and Kheirkhah (2018) considered all the three aspects of sustainable development in a cross-dock related problem. Our work is different from Rezaei and Kheirkhah (2018), as they focus on strategic level decisions in a network design framework, and do not take the effect of operational decisions into account. In addition, their social and environmental criteria are different from those of our research. Furthermore, Tirkolaee et al. (2020) proposed reliability in a PRP with cross-dock selection as customer satisfaction which is considered in the social dimension. The current research is different from the one of Tirkolaee et al. (2020) which considers the strategic decisions of the supply chain. Hamedirostami, Goli, and Gholipour-Kanani (2022)investigated the optimization of cross-dock in sustainable supply chain under uncertainty. They presented a two-objective mathematical model and minimized the costs and the environmental impact of the supply chain.

1.2. Sustainable VRP including social aspect

Many authors concentrate on the environmental aspect of their studies, and overlook the social aspect. Noise pollution is one of the social factors which has an impact on quality of life and health. Ćirović, Pamučar, and Božanić (2014) limited traffic noise level on the road which is affected by the number of passengers, heavy vehicles and buses. In addition, Rahimi, Baboli, and Rekik (2016) considered noise level as a constraint which depends on the route and type of vehicles. Furthermore, Bandeira, Guarnaccia, Fernandes, and Coelho (2018) formulated the varying speed due to acceleration and deceleration as an important factor for calculating noise level.

When the drivers have to wait a long time in the congestion, it leads to the job dissatisfaction. Zhu and Hu (2019) investigated a sustainable routing problem in a congestion situation. In order to avoid heavy congestions, they considered the the drivers' waiting times at the customer's nodes and routes.

On a strategic level, career opportunity is one of the social impacts. Zhalechian, Tavakkoli-Moghaddam, Zahiri, and Mohammadi (2016) discussed the employment level in a location routing problem. Equity among the drivers is studied by Ramos, Gomes, and Barbosa-Póvoa (2014) as another social goal, which helps overloaded drivers to work less than before. Furthermore, Govindan, Jafarian, and Nourbakhsh (2019) investigated job opportunities in a sustainable supply chain with the vehicle routing problem. Also, Shahedi, Nasiri, Sangari, Werner, and Jolai (2021) considered employments opportunity which is created by the establishment of the required facilities.

Accident prevention is another social impact in routing problem. Rahimi et al. (2016) considered accident rate proportional to average traffic speed and vehicle speed on the selected route. Also, Reyes-Rubiano, Calvet, Juan, Faulin, and Bové (2018) studied vehicle load and distance traveled in accident risk. Bandeira et al. (2018) presented a safety model based on empirical GPS data and microscopic simulation. Abdullahi, Reyes-Rubiano, Ouelhadj, Faulin, and Juan (2021) estimated vehicle accidents according to their load and travel distance. Furthermore, Peng, Ji, and Ji (2020) estimated the likelihood of an accident on each route considering the social impact of the load and the type of vehicle. They believe that the social impact of a fully loaded truck is more than an empty one when an accident occurs.

Customer satisfaction is the most frequently studied criterion of the social dimension (Table 1). Freshness of products and food quality, minimization of food waste, and on-time delivery are major factors that customer satisfaction depends on.

Table 1 shows recent studies on sustainable VRP that take the social aspect into account. It should be noted that some researchers investigated economic as well as social aspects, but environmental consideration is neglected. So, we only present researches with all the three dimensions.

Table 1
New researches sustainable VRP with social aspect

Research	Job satisfaction				Noise emission	Customer satisfaction
	Driver's waiting time	Career opportunities	Accident prevention	Equity between drivers		
Ćirović et al. (2014)					✔	
Ramos et al. (2014)				✔		
Afshar-Bakeshloo, Mehrabi, Safari, Maleki, and Jolai (2016)						✔
Rahimi et al. (2016)			✔		✔	✔
Song and Ko (2016)						✔
Tavakkoli-Moghaddam et al. (2016)						✔
Zhalechian et al. (2016)		✔				
Hosseini-Nasab and Lotfalian (2017)						✔
Bandeira et al. (2018)			✔		✔	
Reyes-Rubiano et al. (2018)			✔			
Govindan et al. (2019)		✔				✔
Zhu and Hu (2019)	✔					
Chan et al. (2020)						✔
Peng et al. (2020)			✔			
Qiao et al. (2020)						✔
Alamatsaz et al. (2021)						✔
Abdullahi et al. (2021)			✔			
Shahedi et al. (2021)		✔				
Shahrabi, Tavakkoli-Moghaddam, Triki, Pahlevani, and Rahimi (2022)						✔
Galindres, Guimarães, and Gallego-Rendón (2023)				✔		
This study				✔		✔

The studies reviewed so far reveal some research gaps. Most studies of sustainability in VRP have only Concentrated on economic and environmental aspects of sustainability, leaving out social factors. Moreover, previous studies have not dealt with an operational model for a sustainable cross-dock. To fulfill this shortcomings, this paper presents a new sustainable VRP model using a cross-dock facility incorporating social concerns. Our main contributions that distinguish our efforts from related studies are:
including all the three aspects of sustainability to have a complete foundation of this concept in a cross-dock in the operational level, as routing problem decisions are operational decisions,
obtaining a fair cross-dock schedule for drivers by balancing their working hours to satisfy them as a social responsibility concern; and
Proposing a matheuristic approach which employs the fix and optimize algorithm to solve the problem, which has not been used before to the best of our knowledge.
A cross-docking center is designed to optimize decisions in three areas including scheduling and sequencing of incoming vehicles at receiving doors, scheduling and sequencing of incoming vehicles at shipping doors, and delivery routing to ensure that drivers work fair hours.

1.3. Outline

The continuation of the paper is as follows. In Section 2, we describe the problem and present the mixed-integer linear programming (MILP) model including the objective function and constraints. Section 3 details the solution approach. The experimental results and case study are presented in Section 4. Eventually, Section 5 covers the main and overall conclusions, and also outlines some offers for future research.

2. Problem Description, Notations, and Mathematical Model

This section develops a model for making optimal decisions about a cross-dock which distributes orders of customers. The cross-dock has F receiving dock doors indexed by $f \in \{1, \dots, F\}$ which serve a set of L incoming vehicles indexed by $l \in \{1, \dots, L\}$, and H shipping dock doors indexed by $h \in \{1, \dots, H\}$ which serve a set of K outgoing vehicles indexed by $k \in \{1, \dots, K\}$. In addition, there are n customers (nodes) indexed by $i \in N = \{1, \dots, n\}$, and P product types indexed by $p \in \{1, \dots, P\}$. Customer i has a certain demand of D_{ip} units of product type p, which should be met. The orders of customers are carried by incoming vehicles to the cross-dock parking yard. Next, it takes tt minutes for the incoming vehicle to reach the dock door. It also takes PU_{il} minutes to unload the order of customer i shipped by incoming vehicle l. The orders are then transferred from the receiving dock door to one of the shipping dock doors which takes TRS minutes. At the shipping dock door, the order of customer i is loaded onto an outgoing vehicle k, which takes PL_{ik} minutes. At the beginning of the planning horizon, all of the outgoing vehicles are available at the shipping dock doors. In addition, we are looking for a sustainable routing for outgoing vehicles to leave the cross-dock (indexed by 0 and $n+1$), visit n customers (nodes) and deliver the orders. Each customer visited by only one outgoing vehicle and after delivering orders to the customer j in ST_j minutes they return to cross-dock. To achieve on-time delivery which affects the customer's satisfaction, we consider a time window $[a_i, b_i]$ for each customer i. Therefore, we are penalized by μ or π cost units for a time unit of earliness or tardiness, respectively. Fig. 1 illustrates the proposed problem.

The amount of GHG emissions released due to a liter of fuel consumption is denoted by GHG. Fuel consumption is different from a mountainous road to a flat road. So, we consider θ_{ij} as a road angel between two nodes i and j.

A sustainable VRPCD which the social aspect is the freshness of delivered product p to customer i should be greater than the customer's expected freshness for product p, ex_{ip}. Also, the maximum drivers' working hours $dmax_k$ is minimized in order to improve their job satisfaction. In environmental aspect, GHG emissions are produced by vehicles should not exceed the allowed level, AL. Finally, the total cost, including inventory holding, transportation and penalty whether earliness or tardiness costs are considered in an economic viewpoint.

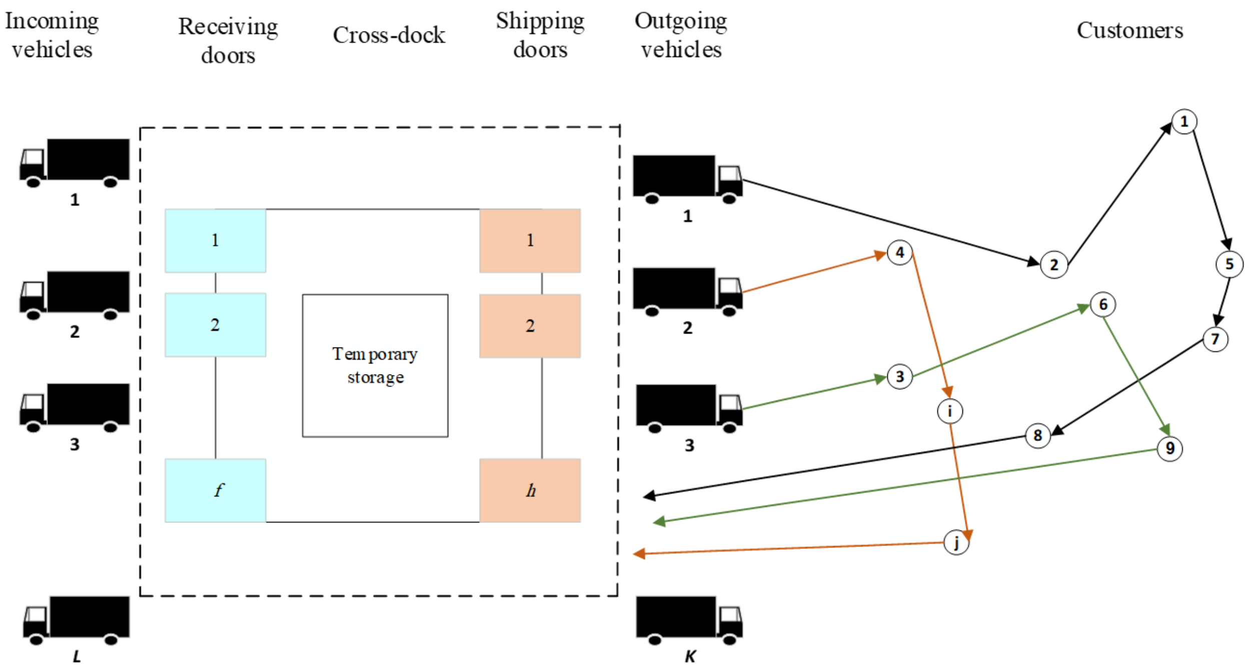

Fig. 1. The outline of the proposed problem

2.1. Assumptions

The following assumptions are made:

1. Temporary storage is unlimited
2. Single depot multi-vehicle problem with delivery time windows and no pickups is considered.
3. All outgoing vehicles are available at zero time
4. Outgoing vehicles travel at a constant speed from node i to j
5. Total customer demand does not exceed total vehicle capacity.
6. The fleet is assumed heterogeneous, i.e., each vehicle has its own capacity, GHG emissions, cost and average speed.
7. The products are fresh.
8. The freshness of products is starting to decrease when theyare unloaded at the cross-dock.
9. The working hours of drivers are calculated when the cross-dock operations are started (at time zero).
10. Emission is a function of air density, vehicle shape and gravity.

2.2. Notations

Set:

N	Set of all nodes including customers and cross dock, $i,j \in N = \{0,1,\dots,n,n+1\}$, the cross dock is indicated by a special node with index 0 or $n+1$
F	Set of receiving doors, $f \in \{1,\dots,F\}$
L	Set of incoming vehicles, $l \in \{0,1,\dots,L,L+1\}$, where $l=0$ and $l=L+1$ define dummy incoming vehicles
K	Set of outgoing vehicles, $k \in \{0,1,\dots,K,K+1\}$, where $k=0$ and $k=K+1$ define dummy incoming vehicles
H	Set of shipping doors, $h \in \{1,\dots,H\}$
P	Set of product types, $p \in \{1,\dots,P\}$

Parameters:

tt	Travel time between parking yard and dock door (in min)
TRS	The time needed to transfer the order from receiving door to shipping door (in min)
u_{il}	Load of incoming vehicle l, 1 if order of customer i is brought by incoming vehicle l and 0 otherwise.
PU_{il}	Time to unload the order of customer i on vehicle l at cross dock (in min)
PL_{ik}	Loading time of order of customer i on vehicle k at cross dock (in min)
$[a_i, b_i]$	Delivery time window for order of customer i (in min)
c_{ijk}	Travel time between nodes i and j with vehicle k (in min)
C_k	Fix cost of vehicle k
δ_{ijk}	Transportation cost from i to j with vehicle k
Q_k	Capacity of vehicle k (in pallets)
WQ_k	Weight capacity of vehicle k (in kilograms)
T	Planning horizon (in min)
D_{ip}	The number of product type p ordered by the customer i (in pallets)
ex_{ip}	The acceptable freshness of product type p for customer i
μ	The cost of earliness penalty ($ per pallet per min)
π	The cost of tardiness penalty ($ per pallet per min)
γ	The cost of inventory holding ($ per pallet per min)
GHG	GHG emissions per liter of fuel consumption
θ_{ij}	The angle formed by the connection of nodes i and j with the horizon line
g	Gravity (meters/square second)
A_k	Frontal surface area (square meters)
ρ	Air density (kilograms/square meter)
Cd	Friction rate of air
w_k	Weight of vehicle k
Cr	Rolling resistance
α	Arc specific constant
β_k	Vehicle k specific constant
V_{ijk}	The speed of vehicle k when travelling from node i to node j
M	Big number
d_{ij}	Distance from node i to node j (in kilometers)
$Budget$	Considered budget on planning horizon
fl_p	Freshness life of product type p
ST_j	The amount of time it takes to unload the order of the customer j
WP_p	Weight of one pallet of product p

Variables:

at_l	Arrival time of the incoming vehicle l at the cross dock
at_i	Arrival time of order of customer i at the cross dock
rt_l	Release time of incoming vehicle l
r_i	Release time of order of customer i
y_{lf}	1 if the incoming vehicle l is processed at the receiving door f and 0 otherwise.
x_{lj}	1 if the incoming vehicles l and j are processed on the same receiving door and l immediately precede j and 0 otherwise.
Y_{kh}	1 if the outgoing vehicle k is processed at the shipping door h and 0 otherwise.
X_{kj}	1 if the outgoing vehicles k and j are processed on the same shipping door and j immediately precede k and 0 otherwise.
p_k	1 if the outgoing vehicle k is used for delivery of orders and 0 otherwise.
z_{ijk}	1 if the outgoing vehicle k travels from node i to j and 0 otherwise.
v_{ik}	1 if the outgoing vehicle k carries the order of customer i and 0 otherwise.
s_{ik}	Time at which the outgoing vehicle k leaves node i
s_i	Time at which the order of the customer i is delivered
DT_k	Time at which the outgoing vehicle k leaves the cross dock
dt_i	Time at which the order of the customer i leaves the cross dock
e_i	Earliness of order of customer i
l_i	Tardiness of the order of the customer i
fr_{ip}	Freshness of product p at node i
lv_{ijk}	Load of vehicle k when travelling from node i to j

2.3. Dimensions of Sustainability

Three aspects of sustainability (i.e., social, economic and environmental) are considered. The social dimension in this study included two important issues. The first social issue is measured through job satisfaction for drivers by minimization of the maximum working hours among all drivers in the planning horizon. This objective, balances work hours and creates equity among the drivers to achieve fair working schedule. So overloaded drivers will work less than before and under-loaded drivers will fulfill this gap. The social objective is formulated in equation (1):

$$\text{Min } dmax_k$$
$$dmax \geq s_{n+1,k} \qquad \forall k \in \{1,2,\dots,K\}, \qquad (1)$$

where dmax is maximum of drivers working hours.

The second social issue is that the freshness of each product should be greater than the allowed amount of freshness for customers. Due to decreasing quality of products by the time from cross-dock to customers, this factor for determining customer satisfaction is considered. There is a limited freshness-life for each product depending on the circumstances. Fig. 2 illustrates the freshness of the product over time. The important assumption in freshness calculation is that products are unloaded at cross-dock with the highest freshness. We employ the same approach as Rahbari et al. (2019). Since expected freshness for each customer is not zero, the authors ignored the function after T'.

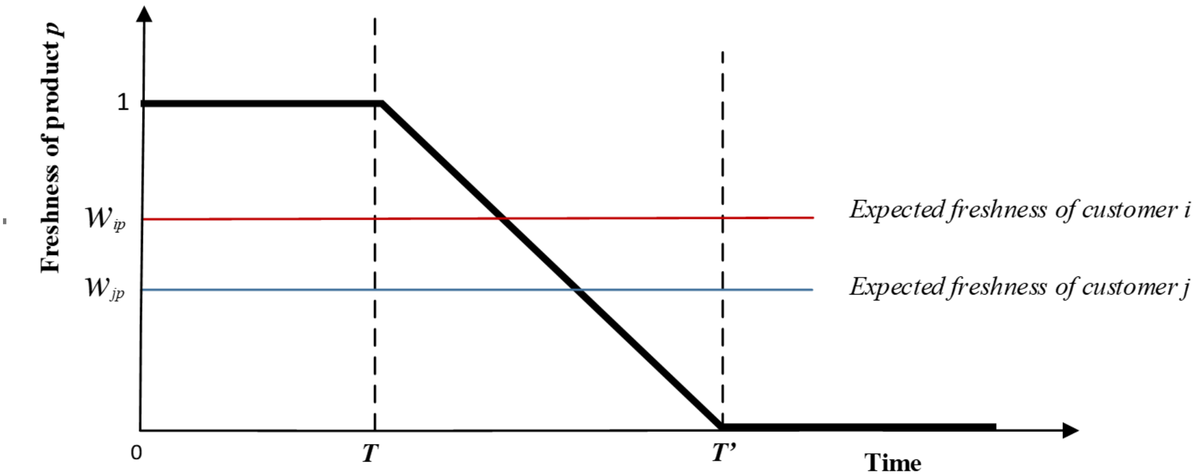

Fig. 2. The freshness of product over time

In Fig. 2, $t = 0$ illustrates the time of product harvest, T is the unloaded time at cross-dock and T' is the time which product lost acceptable freshness. According to Fig. 2 the freshness of the product formulation is:

$$fr_{ip} \geq ex_{ip} \qquad \forall i \in \{1,2,\dots,n\}; p \in \{1,2,\dots,P\}; D_{ip} \neq 0 \qquad (2)$$

$$fr_{ip} = \frac{fl_p - (s_i - r_i)}{fl_p} \qquad \forall i \in \{1,2,\dots,n\}; p \in \{1,2,\dots,P\}; D_{ip} \neq 0 \qquad (3)$$

In this research, the freshness life of product after T' is ignored because the freshness must be greater than a positive threshold (the customer's expected freshness). Constraint (2) states the freshness of delivered any type of product to each customer should be greater than their expectation. Constraint (3) formulates the freshness function as a linear decreasing function. This function starts to decrease when orders are released from cross dock.

In the economic viewpoint, different costs of cross-docking and delivery are taken into account. Indeed, penalty costs, including earliness and tardiness, inventory holding at cross-dock, vehicles fixed costs, transportation cost are considered, respectively. Therefore, constraint (4) ensures that the total costs should not exceed a predetermined budget.

$$Budget \geq \sum_{i=1}^{n} \mu d_i e_i + \sum_{i=1}^{n} \pi d_i l_i + \sum_{i=1}^{n} \gamma (dt_i - rt_i) \sum_{p \in P} D_{ip} + \sum_{k=1}^{K} p_k C_k + \sum_{i=0}^{n} \sum_{j=1, i \neq j}^{n+1} \sum_{k=1}^{K} \delta_{ijk} (z_{ijk} \times c_{ijk}) \qquad (4)$$

The environmental dimension is measured by the GHG (Green House Gas like CO2, CH4, and HFCs) emissions associated with the outgoing vehicles between cross-dock and customers. The fuel consumption and emissions are estimated using the same approach as in Bektaş and Laporte (2011). According to this model, the total amount of GHG from node i to j is measured as equation (5) which should be less than allowed emissions. Based on the recommendations by the WHO, the limit values of the input parameter variables AL were defined, which are characterized as the greatest and highest allowed values of the given parameters.

$$GHG \sum_{i=0}^{n}\sum_{j=1}^{n+1}\alpha d_{ij}\sum_{k=1}^{K}\left((w_k z_{ijk})+lv_{ijk}\right)+\sum_{i=0}^{n}\sum_{j=1}^{n+1}\beta_k d_{ij}\sum_{k=1}^{K}V_{ijk}^2 z_{ijk} \leq Al \tag{5}$$

where $\alpha = gsin\theta_{ij} + g * Cr * cos\theta_{ij}$ is an arc specific constant and $\beta = 0.5 * Cd * A_k * \rho$ is a vehicle specific constant. The first component measures the cost incurred by the load carried on the vehicle and the second component measures the cost implied by the speed of vehicle k. The other constraints are as follows:

$$\sum_{k=1}^{K}\sum_{i=0,i\neq j}^{n} z_{ijk} = 1 \qquad \forall J \in \{1,2,\dots,n\} \tag{6}$$

$$\sum_{j=1}^{n} z_{0jk} = 1 \qquad \forall k \in \{1,2,\dots,K\} \tag{7}$$

$$\sum_{i=1}^{n} z_{i,n+1,k} = 1 \qquad \forall k \in \{1,2,\dots,K\} \tag{8}$$

$$\sum_{j=1}^{n} z_{jik} - \sum_{j=1}^{n+1} z_{ijk} = 0 \qquad \forall k \in \{1,2,\dots,K\}; i \in \{1,2,\dots,n\} \tag{9}$$

$$s_i \leq T \qquad \forall i \in \{1,2,\dots,n\} \tag{10}$$

$$DT_j \geq DT_k + \sum_{i=1}^{n} PL_{ij}\, v_{ij} - M\left(1 - X_{kj}\right) \qquad \forall k,j \in \{1,\dots,K\}; k \neq j \tag{11}$$

$$s_i - b_i \leq l_i \qquad \forall i \in \{1,2,\dots,n\} \tag{12}$$

$$a_i - s_i \geq e_i \qquad \forall i \in \{1,2,\dots,n\} \tag{13}$$

$$s_{jk} \geq s_{ik} + c_{ijk} + ST_j - M(1 - z_{ijk}) \qquad \forall i \in \{0,1,\dots,n\};\ \forall i \in \{1,2,\dots,n+1\};\ i \neq j; k \in \{1,2,\dots,K\} \tag{14}$$

$$s_i \geq s_{ik} - M(1 - v_{ik}) \qquad \forall k \in \{1,2,\dots,K\}; i \in \{1,2,\dots,n\} \tag{15}$$

$$s_i \leq s_{ik} + M(1 - v_{ik}) \qquad \forall k \in \{1,2,\dots,K\}; i \in \{1,2,\dots,n\} \tag{16}$$

$$\frac{1}{M}\sum_{i=0,i\neq j}^{n} z_{ijk} \leq v_{jk} \leq \sum_{i=0,i\neq j}^{n} z_{ijk} \qquad \forall k \in \{1,2,\dots,K\}; j \in \{1,2,\dots,n\} \tag{17}$$

$$\sum_{i=1}^{n} D_i\, v_{ik} \leq Q_k \qquad \forall k \in \{1,2,\dots,K\} \tag{18}$$

$$DT_k \geq r_i + PL_{ik} + TRS - M(1 - v_{ik}) \qquad \forall k \in \{1,2,\dots,K\}; i \in \{1,2,\dots,n\} \tag{19}$$

$$dt_i \geq DT_k - M(1 - v_{ik}) \qquad \forall k \in \{1,2,\dots,K\}; i \in \{1,2,\dots,n\} \tag{20}$$

$$\sum_{h=1}^{H} Y_{kh} = 1 \quad \forall k \in \{1,2,\dots,K\} \tag{21}$$

$$\sum_{f\in F} y_{lf} = 1 \quad \forall l \in \{1,2,\dots,L\} \tag{22}$$

$$x_{lj} - 1 \le y_{lf} - y_{if} \le 1 - x_{lj} \quad \forall l,j \in \{1,2,\dots,L\};\ l \neq j;\ \forall f \in \{1,2,\dots,F\} \tag{23}$$

$$r_i \ge rt_l \quad \forall l \in \{1,2,\dots,L\}; i \in \{1,2,\dots,n\}\,; u_{il} = 1 \tag{24}$$

$$rt_l = at_l + tt + \sum_{i=1}^{n} PU_{il} \quad \forall l \in \{1,2,\dots,L\} \tag{25}$$

$$rt_j \ge rt_l + \sum_{i=1}^{n} PU_{il} - M(1 - x_{lj}) \quad \forall l,j \in \{1,2,\dots,L\}; l \neq j \tag{26}$$

$$\sum_{j=0,j\neq i}^{n} f_{jik} - \sum_{j=1,j\neq i}^{n+1} vl_{ijk} = \sum_{p=1}^{P} WP_p D_{ip} \quad \forall k \in \{1,2,\dots,K\}; i \in \{1,2,\dots,n\} \tag{27}$$

$$\left(\sum_{p\in P} WP_p D_{jp}\right) z_{ijk} \le vl_{ijk} \le (WQ_k - \sum_{p\in P} WP_p D_{ip}) z_{ijk} \quad \forall i \in \{0,1,\dots,n\};\ i \in \{1,2,\dots,n+1\}; i \neq j;\ k \in \{1,2,\dots,;\} \tag{28}$$

$$\sum_{l=0,l\neq j}^{L} x_{lj} = 1 \quad \forall J \in \{1,2,\dots,L\} \tag{29}$$

$$\sum_{j=1,l\neq j}^{L+1} x_{lj} = 1 \quad \forall l \in \{1,2,\dots,L\} \tag{30}$$

$$x_{0j} + x_{0l} + y_{lf} + y_{jf} \le 3 \quad \forall l,j \in \{1,2,\dots,L\};\ l \neq j; f \in \{1,2,\dots,F\} \tag{31}$$

$$(X_{kj} - 1) \le Y_{kh} - Y_{jh} \le (1 - X_{kj}) \quad \forall k,j \in \{1,2,\dots,K\}; h \in \{1,2,\dots,H\};\ k \neq j \tag{32}$$

$$\textstyle\sum_{k=0,j\neq k}^{K} X_{kj} = 1 \quad \forall j \in \{1,2,\dots,K\} \tag{33}$$

$$\textstyle\sum_{j=1,j\neq k}^{K+1} X_{kj} = 1 \quad \forall k \in \{1,2,\dots,K\} \tag{34}$$

$$X_{0k} + X_{0j} + Y_{kh} + Y_{jh} \le 3 \quad \forall k,j \in \{1,2,\dots,K+1\}; h \in \{1,2,\dots,H\};\ k \neq j \tag{35}$$

$$v_{ik} \le p_k \quad \forall k \in \{1,2,\dots,K\} \tag{36}$$

$$DT_k = s_{0k} \quad \forall k \in \{1,2,\dots,K\}; i \in \{1,2,\dots,n\} \tag{37}$$

$$y_{lf} \in \{0,1\} \quad \forall l \in \{0,1,\dots,L+1\}\,;\ f \in \{1,2,\dots,F\}$$

$$x_{lj} \in \{0,1\} \quad \forall l \in \{0,1,\dots,L\};\ j \in \{1,2,\dots,L+1\}; l \neq j$$

$$Y_{kh} \in \{0,1\} \quad \forall k \in \{1,2,\dots,K+1\}; h \in \{1,2,\dots,H\}$$

$$X_{kj} \in \{0,1\} \quad \forall j \in \{1,2,\dots,K+1\}; k \neq j;\ k \in \{0,1,\dots,K\}$$

$$z_{ijk} \in \{0,1\} \quad \forall i \in \{0,1,\dots,n\};\ j \in \{1,2,\dots,n+1\}; i \neq j; k \in \{1,2,\dots,K\}$$

$$v_{ik} \in \{0,1\} \quad \forall k \in \{1,2,\dots,K\}; i \in \{1,2,\dots,n\}$$

Constraint (6) states that every node is served once by a vehicle. Constraint (7) restricts each delivery route which should be started at the cross-dock. Each route should end at the cross-dock due to the constraint (8). Constraint (9) specifies how the outgoing vehicle's route of delivery will be scheduled. Each delivery order must be completed within the planning horizon according to constraint (10). Constraint (11) calculates departure time of vehicle j, if vehicle j leaves cross-dock after k, immediately. Constraints (12) and (13) evaluate earliness and tardiness of customer i. Constraint (14) calculates leaving time of node j, if vehicle k leaves node j after node i, immediately. Constraints (15) and (16) imply delivery time for orders of each customer. Constraint (17) enforces $v_{jk} = 1$, if vehicle

k carries order j. Constraint (18) ensures that the transported freight between two nodes should be less than the capacity of the vehicle. Constraint (19) implies that departure time of vehicle k should be greater than release time of order i if vehicle k carries out order i. Constraint (20) guarantees that departure time of order i at cross-dock should be greater than departure time of vehicle k at cross-dock, if vehicle k carries out order i. In accordance with constraint (21) every outgoing vehicle should be processed at only one shipping door. Constraint (22) stipulate that an incoming vehicle should be processed at one receiving door only. Constraint (23) makes sure that when one incoming vehicle arrives before another, they must be at the same receiving door. Constraint (24) states incoming vehicle release time. Constraint (25) restricts the incoming truck release time that should be greater than arrival time. Constraint (26) ensures release time of incoming truck j should be greater than arrival time of incoming vehicle l, if vehicle j is processed after l, immediately. Constraints (27) and (28) restrict the arc flows. Constraint (29) guarantees that every incoming vehicle is exactly preceded by one incoming vehicle. Constraint (30) ensures that every incoming vehicle is exactly followed by one receiving. Constraint (31) specifies that if both incoming vehicle l and incoming vehicle j come right after incoming vehicle 0, they have to be allocated to separate receiving doors. Constraint (32) ensures that, when one outgoing vehicle precedes another, they must be at the same shipping door. Constraint (33) guarantees that every outgoing vehicle is exactly preceded by one outgoing vehicle. Constraint (34) ensures that each outgoing vehicle has exactly one succeeding shipping. The constraint (35) states that if both outgoing vehicles k and j are immediately following outgoing vehicle 0, they must be on separate outgoing doors. Constraint (36) ensures that if vehicle k is used, the related variable should be 1. Constraint (37) states that the departure time of vehicle k at cross-dock is release time of vehicle k at node 0.

3. Solution Approach

In this section, we propose a matheuristic algorithm to solve large-sized problems. Matheuristic as its name suggests is the hybridization of mathematical programming with metaheuristics. The proposed hybrid algorithm is a combination of mixed integer programming (MIP) and the genetic algorithm (GA), and hereafter we call it MGA. The GA was introduced by Holland (1975) for the first time. GA is an evolutionary search method where an initial set of solutions is improved over successive generations using genetic operators. This method is most effective in situations where the search space is not well-defined. In GA, each individual or chromosome is represented by a structure that captures the values of the decision variables of the problem. These individuals together form the population, and the chromosomes develop over successive iterations known as generations. In each generation, the chromosomes are evaluated for their fitness using specific measures. When the problem becomes more complicated, considering all the decisions in the chromosomes and preserving the feasibility of the solutions becomes very difficult. Therefore, some of the decisions can be made within a mathematical model (usually a MIPmodel). In the proposed approach, the decisions determined by each chromosome are transferred into an MIP model as the input (Sub-problem 1), where the other decisions are made by minimizing the objective function subject to some constraints. Then, the objective function value is returned to the GA to be used as the fitness value of that particular chromosome. Each of the individuals determines the values for the variables of the problem. Sub-problem 1 and the steps of the matheuristic are presented in Fig. 3.

Sub-problem 1:

Minimize $dmax_k$

Subject to:

Constraints (2)-(5), (10)-(20), (24)-(28) and (36)-(37)

Step 1: Set the parameters
Step 2: Initialization:
    Initialize the population.
Step 3: Evaluation:
    For every individual, determine values of y_{lf}, x_{lj}, X_{kj}, Y_{kh}, v_{ik} and z_{ijk}.
    Using the above values as the parameters, solve Sub-problem 1 and return the optimal value of $dmax_k$ as the fitness of the individual.
Step 4: If the termination condition is satisfied go to step 7 otherwise go to step 5.
Step 5: Select the best solution among the entire population as parents, use cross-over and mutation operators to generate the new population as offspring.
Step 6: Go to step 3.
Step 7: Output the best solution.

Fig. 3. The matheuristic pseudo code

3.1. Chromosome design

In GA terminology, a chromosome is an array that represents a candidate solution. In this case, the chromosome is a $L+F+H+K+2n-2$ array which is randomly generated. In the array, the assignment of each receiving/shipping vehicle to receiving/shipping doors and the sequence of each vehicle is shown. This chromosome has four segments: the first segment is related to the sequence and assignment of incoming vehicles. The integer numbers between 1 to $L+F-1$ are generated randomly. The second segment is related to customers which is generated randomly. The third segment is related to sequence and assignments of outgoing vehicles. The integer numbers between 1 to $K+H-1$ is generated randomly. The fourth segment is related to the priority of customers.

For example, consider a problem with four incoming vehicles ($L=4$), two receiving dock-doors ($F=2$), five shipping vehicles ($K=5$), two shipping dock-doors ($H=2$) and eight customers ($n=8$). Fig. 4 illustrates the chromosome of this example. This chromosome tells us the sequence and assignment of receiving/shipping vehicles in receiving/shipping dock-doors and the sequence of customers. The numbers that are greater than the number of vehicles separate dock-doors from each other. The first position which its value is greater than four is third position. So, vehicles number 4 and 1 are processed on receiving dock-door number 1, respectively, i.e. $y_{41}=1$, $y_{11}=1$, $x_{04}=1$, $x_{41}=1$ and $x_{15}=1$. Vehicles number 2 and 3 are processed on receiving dock-door number 2, respectively.

The second segment is related to customer's node. For third segment, the other sequence and assignment of outgoing vehicles are same as incoming vehicles procedure.

To decoded v_{ik} , the first three segments of chromosome are considered. using FCFS rule, the products are transferred from incoming vehicle l to outgoing vehicle k based on the truck sequence. In this example, the products carried by incoming vehicle 4 are firstly assigned to outgoing vehicle 1 based on customer sequence, as required. The next outgoing vehicles in the shipping sequence (3, 4, 2 and 5 respectively) pick up the remaining products from incoming vehicle 4 if required, until all products are assigned. These steps are carried out again for the next arriving vehicles (1, 2, and 3, respectlively) until all the incoming goods are assigned to outgoing vehicles. Incoming vehicle 4 arrived with orders 2, 3, and 8.Outgoing vehicle 1 picks up order 2 according to the order sequence. Outgoing vehicle 3 picks up order 3, also order 8 is allocated to outgoing vehicle 3 i.e. $v_{21}=1$, $v_{33}=1$ and $v_{83}=1$. Fig. 5 demonstrates this example.

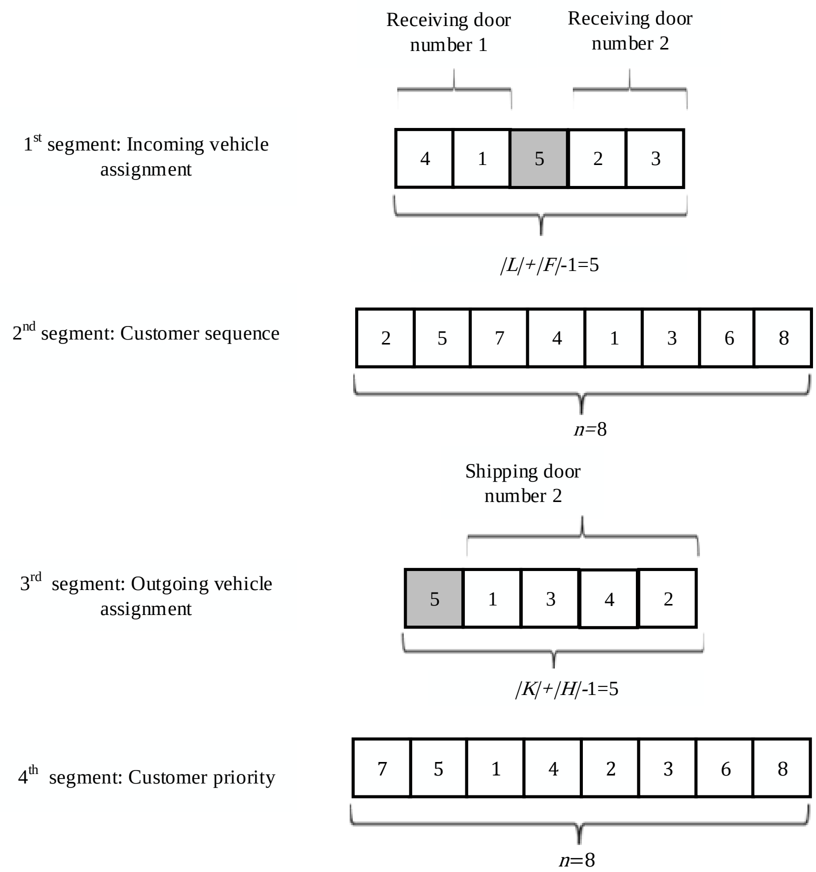

Fig. 4. Solution representation for an example

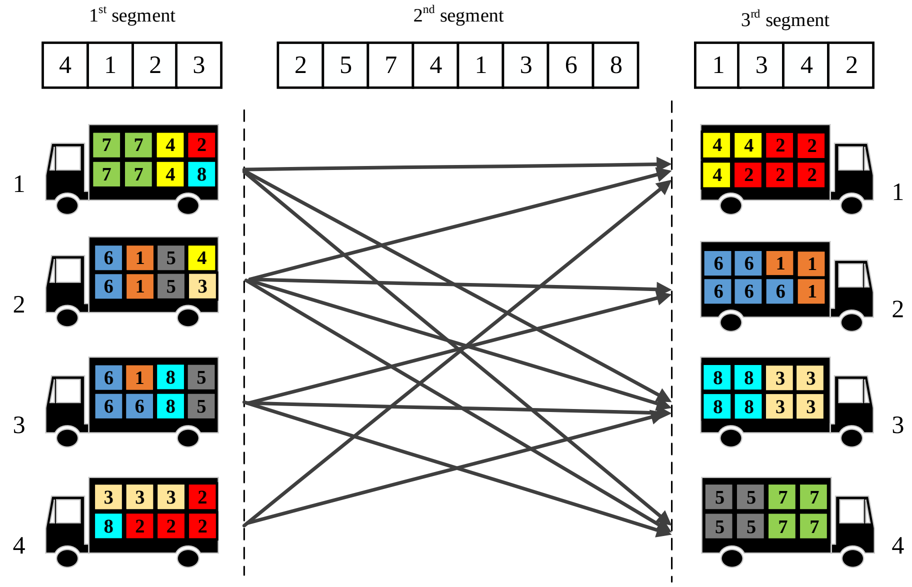

Fig. 5. An example of product transfer method using FCFS rule

To decode z_{ijk} , the fourth segment of the chromosome is considered. The products are assigned to the outgoing vehicle in previous step. Now, customer sequence for each truck should be determined. In this example, outgoing vehicle 1 carries orders of customers 4 and 2. In 4th segment, priority of customer 4 is higher than customer 2. So outgoing vehicle 1 first visits customer 4. It should be noted that 4th segment is used to generate different solutions.

3.2. Evaluation

In genetic algorithm for evaluation of random chromosome quality, a fitness function is considered. The fitness function minimizes the maximum working hours for drivers.

3.3. Selection procedure

At this stage of the algorithm, the well-known standard roulette wheel selection method is utilized for selection. In order to start the crossover stage, a number of chromosomes are selected from the initial population.

3.4. Crossover

The crossover operator is utilized to create different chromosomes and explore the solution space more comprehensively. The specific crossover applied is a modification of the standard one-point crossover operator and is detailed in Figure 6. By considering the assumed probability of crossover, we semi-randomly select the genes that will be influenced from each parent chromosome. First, generate a random number between 1 and 4, according to segments of the chromosome. Second, according to random number, apply the cross-over operator. For instance, for random number 1, cross-over is applied in first segment of chromosome, other segments will be unchanged. Fig. 6 illustrates the proposed cross-over performance. The genes (trucks) from parent 1 before cross-over point, will be copied on child 1, remaining genes of child 1 for first segment are affected by parent 2. For child 2, the genes before cross-over point will be copied from parent 2. Parent 1 will affect the remaining genes of child 2. We replace the children with parents if they optimize the fitness of the parents. The others will be the same.

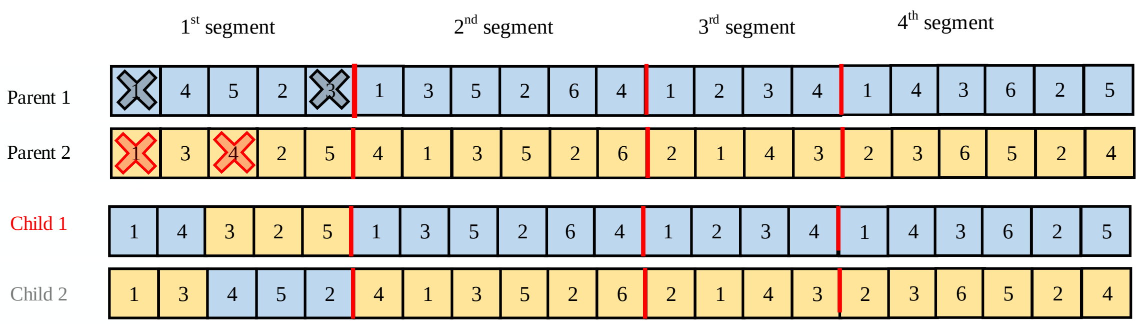

Fig. 6. Single-point crossover

3.5. Mutation

The implemented mutation is used to replace a gene with another gene in the same chromosome. The probability of gene selection is the same. As previously mentioned, a random number is generated. If the random number is 2, the mutation involves selecting a subset of two genes from the chromosome's node string and exchanging them. Figure 7 illustrates the proposed mutation operator using a numerical instance.

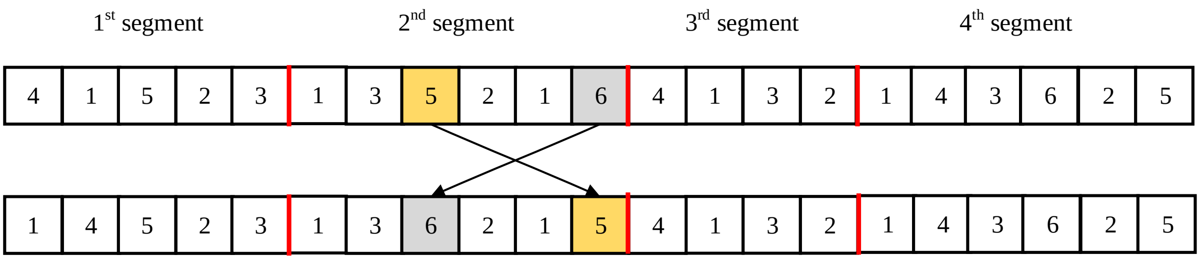

Fig. 7. Mutation operator

3.6. Termination criteria

In this paper, the modified GA terminates when the number of function evaluations reaches the maximum value (Max NFE). This method is a combination of mathematical programming and metaheuristics, so a smaller NFE can be reached in a reasonable time.

4. Computational Results

In this section, we present numerical results on the performance of the proposed Matheuristic. The algorithm has been coded using MATLAB and GAMS software. First, parameter setting and test problems are discussed. Then, a real case study is presented to show how the model can be applied in real-word situations.

4.1. Parameter setting

Only searching and solution representation procedures do not affect the performance of the proposed algorithms, also parameter setting is important for finding well solution and convergence. The Taguchi method is used to establish suitable values for the GA parameters. The initial tests are performed using three distinct values for every parameter. The parameters are crossover rate, mutation rate and population size. For small and large-sized problems, three levels of parameters are proposed. The levels of these parameters are shown in Table 2. A crossover rate of 0.3, a mutation rate of 0.5, and a population size of 30 are set for the GA parameters for problems.

Table 2
Selected levels of parameters in Taguchi experiment.

Levels	Parameters		
	Population size	Crossover rate	Mutation rate
1	15	0.1	0.3
2	30	0.3	0.5
3	50	0.5	0.7

4.2. Test problems

To validate the suggested mathematical formulation and meta-heuristic algorithm, experiments are set up in different operating scenarios. The test problems are categorized into two groups: 1) small problems 1-10 and 2) large problems 11-20. We use small-size demonstrations to extract key insights from the results, while we use large implementations to evaluate how well the proposed algorithm performs. Furthermore, a case study is applied to know the performance of the solution. We should note that the small-sized problems are subset of the case study.
Our objective is to obtain the solution quality rather than solution speed. Using the mathematical programming in the solution method, leads to a slower fitness evaluation while at the same time, the mathematical programming prevents generation of infeasible solutions and does not require the repair process or penalty methods. In small-sized problems, to validate the solution method, we first compute the objective function's value for the specific NFE (300) in GA. Then CPLEX solver is executed to obtain a solution around the the objective function's value obtained from GA. Then the value of relative error (RE) is calculated according to equation (38):

$$RE = \frac{O.F. - X}{X} \times 100 \tag{38}$$

$O.F.$ is the best value of the objective function found by the algorithm.
X is the optimal value of the objective function (lower bound) in CPLEX in small size (large size) problems.
The small amount of RE indicates the efficiency of the proposed algorithm in small dimensions due to the lower execution time than the execution time of CPLEX.

To validate on a large scale, we run CPLEX for 3600 seconds and then run GA with NFE = 500. The results show that for some cases CPLEX has not been able to find an answer during this time, and for some that have been answered, the result of the MGA algorithm has better quality. In addition, the lower bound of CPLEX has been used to calculate RE.

In this section, 20 problems are randomly-generated and solved. The obtained results are presented. Tables 3 and 4 show the results for the small-sized and large-sized problem instances, respectively.

Table 3
The objective function values and CPU times in small-sized problems

Instance	Solution of models								RE
					CPU time (s)		O.F.		
	l	k	p	n	CPLEX	MGA	CPLEX	MGA	
1	3	5	3	8	272	204	214.2	214.2	0
2	4	4	4	9	298	116	238.1	238.1	0
3	4	5	5	8	334	244	223.4	223.9	0.2%
4	3	3	4	9	251	101	243.2	243.7	0.2%
5	3	5	4	10	521	187	232.3	232.3	0
6	3	4	5	8	241	103	225.4	225.4	0
7	4	5	3	9	463	350	230.1	230.1	0
8	3	4	5	9	301	211	232.4	232.7	0.1%
9	4	4	3	10	479	202	241.8	241.8	0
10	4	5	5	10	875	228	236.4	236.8	0.1%
Average									0.06%

Table 4
The objective function values and CPU times in large-sized problems

Instance	Solution of models									RE
					CPU time (s)		O.F.			
	l	k	p	n	CPLEX	MGA	CPLEX	MGA	L.B.	
11	5	6	8	17	3600	827	247.2	242.7	240.4	0.9%
12	6	7	7	18	3600	954	-	237.9	234.2	1.5%
13	7	7	9	17	3600	897	-	224.8	220.9	1.7%
14	6	6	8	15	3600	714	221.5	214.1	212.8	0.6%
15	6	6	7	19	3600	934	-	231.8	230.9	0.2%
16	7	6	8	16	3600	732	268.1	223.9	222.0	0.8%
17	6	7	9	18	3600	901	-	241.9	239.7	0.4%
18	5	6	7	19	3600	912	-	234.8	231.6	1.3%
19	5	5	7	15	3600	724	217.6	231.2	213.2	0
20	5	7	8	16	3600	748	264.1	220.1	218.9	0.5%
Average										0.79%

4.3. *Case study*

To examine if the suggested method can be used in real-world scenarios, a practical case study is presented.This case illustrates the application of the model to route vehicles in Tehran. The underlying transportation network includes a cross-dock which is located in Shahre-Qods and 20 customers. A 20 years old company with a cross dock and some farms around the town is considered. Some vehicles are devoted to transfer vegetables from different farms to cross dock. In the cross dock, five types of vegetables are combined together according to customer's orders. Each product has a descending freshness. At the early stages, the products keep their freshness at the high level until arriving to cross dock. As products are fresh and time windows is considered, the presence of sorting and combination system to accelerate delivery time is unavoidable. Six heterogeneous vehicles are ready at the starting time to carry the orders to Tehran city. Customer locations are in Tehran's city center. Fig. 8. illustrates the location of the cross-dock and the customers in the city. It should be noted that Tehran is a large city, and the distances between the black circles are at least several kilometers

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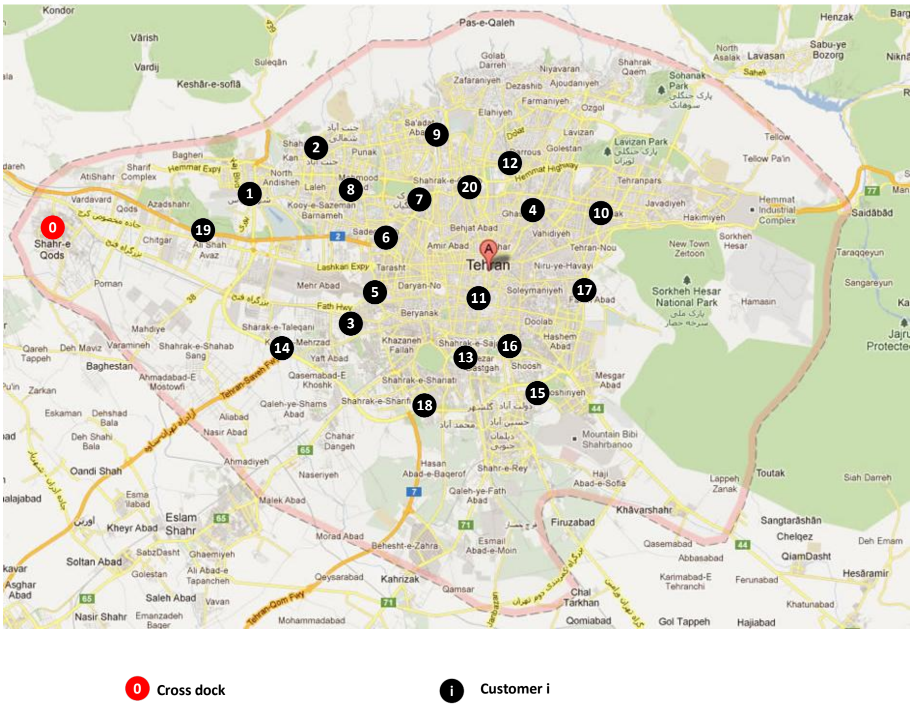

Fig. 8. The dispersion of the customer nodes.

Five perishable products should be transferred to customer nodes by three different types of vehicles to satisfy demands of customers. The freshness of products decreases with time. Travel times (illustrated in Table 5) are provided by using Google Maps. The cross-dock operations are started at 6:30 AM.

Table 5
Travel time between two nodes via google map

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
0	44	60	62	80	65	78	82	63	65	90	70	95	75	40	75	78	80	48	40	86	0
1	0	6	10	20	8	10	15	8	10	30	20	20	24	12	39	25	43	21	6	23	38
2	6	0	25	26	20	17	18	12	8	26	22	20	33	26	40	30	36	32	15	16	44
3	11	28	0	15	8	12	19	17	24	26	10	30	13	12	19	17	24	11	16	24	40
4	19	28	18	0	15	13	10	18	21	12	8	15	16	31	21	8	14	21	36	6	50
5	8	24	10	18	0	8	12	13	19	16	10	24	12	17	24	20	25	14	17	20	42
6	16	16	10	12	8	0	8	9	14	23	12	25	20	28	32	16	28	24	20	16	47
7	18	16	23	14	13	10	0	10	15	23	16	16	24	36	31	16	26	30	36	9	50
8	12	15	20	20	15	12	11	0	11	32	20	29	26	30	36	23	30	30	21	19	44
9	12	10	21	20	20	16	16	14	0	25	26	15	32	36	36	26	33	34	27	11	49
10	32	30	30	12	17	28	23	35	25	0	19	11	20	36	17	11	9	24	41	13	69
11	20	23	12	8	10	10	18	20	24	20	0	22	9	24	19	9	17	13	29	15	45
12	28	24	34	18	22	29	19	26	15	12	22	0	28	43	21	17	19	26	42	9	70
13	28	36	13	20	14	20	21	26	32	22	10	28	0	24	16	11	14	10	31	21	43
14	10	22	15	35	15	30	32	32	36	34	22	43	24	0	31	29	36	14	13	41	36
15	48	40	21	24	23	35	36	34	38	17	20	20	17	32	0	12	9	19	34	30	56
16	20	30	17	8	20	18	17	23	27	10	10	19	10	30	14	0	13	19	31	20	47
17	50	35	21	11	26	25	28	30	33	10	18	20	14	37	10	14	0	28	41	20	60
18	26	30	11	20	13	26	30	29	35	24	13	27	10	14	20	20	28	0	30	29	40
19	9	18	20	40	18	20	34	21	26	40	27	40	32	13	32	32	41	31	0	34	35
20	27	19	24	8	22	20	9	20	11	15	15	10	21	41	30	21	20	32	37	0	53

There are six incoming vehicles and six outgoing vehicles as the transportation system. In addition, there are three receiving dock doors for unloading purposes, and three shipping dock doors for loading the consolidated shipments into the outgoing vehicles. The other parameters are given in Table 6. In addition, the parameter values related to carbon dioxide emissions are extracted from Bektaş and Laporte (2011).

Table 6
Parameters of the case study

$\mathrm{PL}_{ip} = D_{ip}$	$fl_p = [220\ 250\ 300\ 300\ 500]$	$\pi = 0.3$	$\mu = 0.1$
$\delta_{ijk} = 0.1$	$w_k = [5\ 6\ 7\ 5\ 6\ 7]*1000$	$a_i = U[20{,}160]$	$PU = 15$
$Budget = 2000$	$Q_k = [20\ 22\ 25\ 20\ 22\ 25]$	$T = 1440$	$b_i = a_i + U[20{,}40]$
$\gamma = 0.4$	$C_k = [20\ 30\ 40\ 20\ 30\ 40]$	$tt = 5$	$ST_j = \sum_p D_{ip}$

The objective of the problem is to make optimum decisions about sequencing, scheduling and routing of vehicles to minimize the maximum working hours of drivers (load leveling of working hours). Additionally, time windows are used for limiting the acceptable arrival time and determining penalty costs for earliness and tardiness services. Considering freshness and time windows together may seem redundant, but the freshness life has a different function and tries to make the model select shorter routes.
Since, our algorithm is fix and optimize algorithm, we applied our model in MATLAB and CPLEX (generating variables in MATLAB and optimize them in CPLEX). Once we implemented the algorithm to the case study with fix and optimize approach. We have some binary variables which are generated in MATLAB except z_{ijk}. As this decision should be made at CPLEX, so we can have optimization in CPLEX. We should note z_{ijk} represents sequence of customers for each vehicle. The fourth part of the chromosome in fig 4. Belongs to z_{ijk} generation. So, we implemented MGA to the case study without the fourth segment of chromosome. This algorithm is without the order of the customers in the chromosome (fourth part) and considering it in CPLEX software in order to optimize it is mentioned MGA. Furthermore, we applied algorithm with considering z_{ijk} at chromosome at equal times (GA).
Then the convergence diagrams of this algorithm are illustrated for both GA and MGA in Fig. 9. It is observed that in long term decisions when the order of the customers is optimized in CPLEX, better results are obtained compared to the case that all the decisions are made in GA. Also, Table 8 shows the vehicle routing and scheduling at the cross-dock. Furthermore, the routing of vehicle is displayed in Fig. 10.

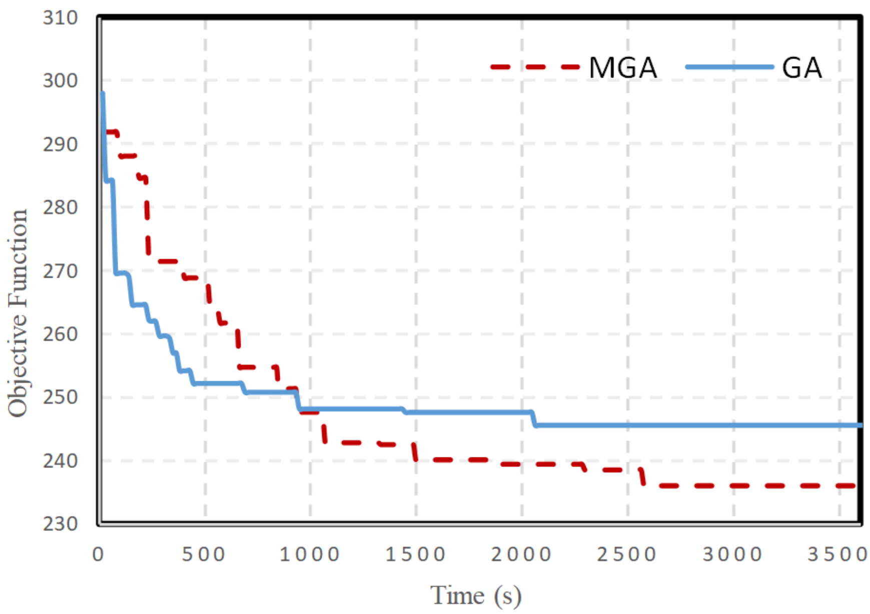

Fig. 9. The convergence of the proposed GA and MGA for the case study.

Table 7
The schedule resulted from optimizing OF $(OF = 236, total\ cost = 472)$

Receiving Door	Sequence (schedule) of incoming vehicles	Shipping door	Sequence (schedule) of outgoing vehicles	outgoing vehicle	Visited nodes (schedule)
1	3 (0) ➝ 1 (20)	1	2 (35)➝ 1 (69)	1	0 (80) ➝ 18 (132) ➝3 (150)➝ 11 (161)➝ 4(174)➝ 21 (228)
2	4 (0) ➝ 2 (20)	2	4 (45)	2	0 (65) ➝ 19 (105) ➝ 20 (139) ➝ 10 (154) ➝ 12 (165) ➝9 (183)➝ 21 (236)
3	5 (0) ➝ 6 (20)	3	3 (20)➝ 5 (67)	3	0 (65) ➝ 1 (121) ➝ 8 (136) ➝ 7 (154) ➝ 6 (171)) ➝ 5 (186) ➝ 21 (233)
				4	0 (65) ➝ 15 (147) ➝ 17 (157) ➝ 16 (172) ➝ 13 (183) ➝ 21 (230)
				5	0 (80) ➝ 14 (120) ➝ 2 (147) ➝ 21 (198)
				6	Not used

Table 7 showcases how the scheduling and sequencing of incoming and outgoing vehicles are strategically planned to minimize the maximum working hours of drivers while ensuring a smooth flow of operations. This table presents the optimized schedule derived from the objective function with a value of 236 and a total cost of 472. The table outlines the organized flow of incoming and outgoing vehicles at the facility, along with the sequence of visits to various nodes. Furthermore, according to Table 8 and Figure 10 for illustration, outgoing vehicle 1 begins its journey from the cross dock at time 80 and stops at nodes 18, (at 132 minutes), 3, (at 150 minutes), 11, (at 161 minutes), and 4 (at 174 minutes), in that order. After that, it returns to the cross dock.

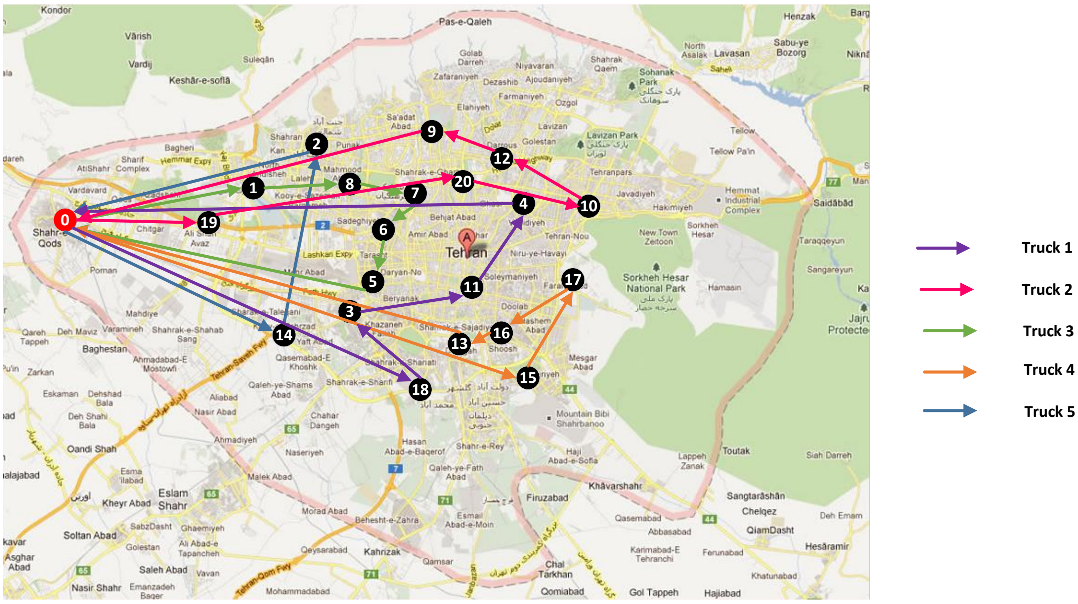

Fig. 10. The routing of vehicles based on case study optimization

4.4. The reduced case study

The experiments for the sensitivity analysis should be conducted by solving an exact method. Since the size of case study is very large to be solved, the number of customers, vehicles (both incoming and outgoing) and 1dock doors are reduced to 9, 3 and 2, respectively. Also, it should be noted that budget is decreased to 300. Other parameters are as same as mentioned in Table7.

4.5. The impact of freshness life changes

To evaluate the outcomes of our mathematical modeling, we made adjustments to the average freshness life of the products. We notice a large leveling effect on the drivers' workload when we simultaneously increase the freshness life across all products, as illustrated in Fig. 11. This adjustment helps distribute tasks more evenly, reducing the peaks and troughs in their daily responsibilities. This modification also impacts the total costs associated with earliness and tardiness. To be more precise, the costs of delivering products early (earliness) tend to rise while the costs of late deliveries (tardiness) tend to decrease as the freshness life grows.

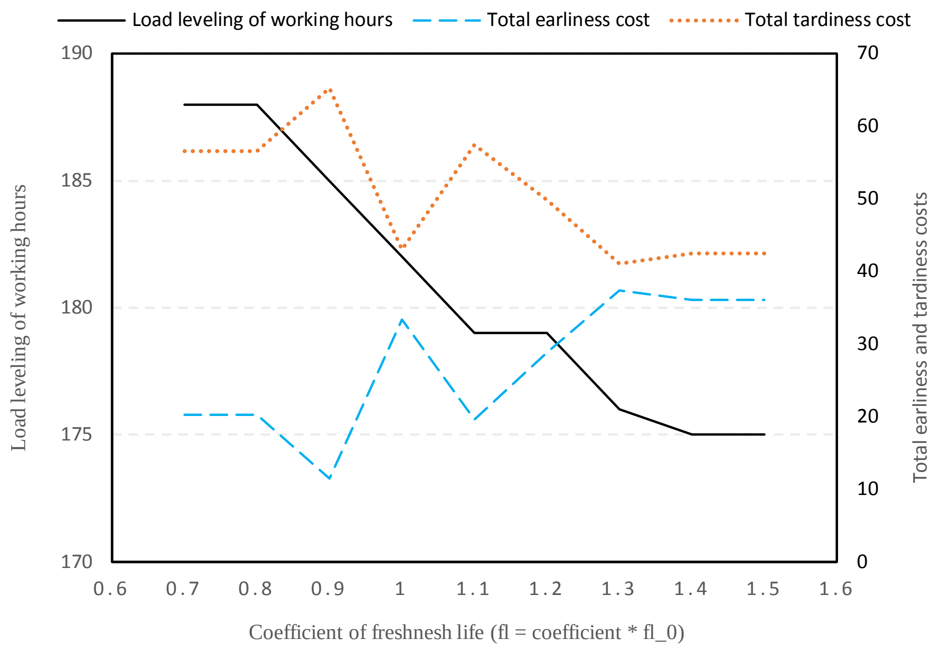

Fig. 11. The impact of freshness life changes on objective function

With the baseline freshness life indicated as fl_0in Table 7, Figure 10 shows how differences in product freshness life affect the objective function. We observe a comparable drop in the objective function value as we extend the products' freshness life. This link implies that improving freshness life has a beneficial impact on the system's overall effectiveness.

The increase in freshness life effectively expands the solution space, allowing for a wider range of potential solutions to be considered. Consequently, this allows the model to investigate additional answers that optimize objective function. As a result, the optimal objective function value decreases due to this larger solution space, suggesting that the system might produce better results with longer freshness lifetimes for the products. The significance of product lifespan in enhancing operational performance is shown by this discovery.

4.6. The impact of budget changes

Another key factor we adjusted to illustrate the application of our model is the budget. Changes to the budget, as shown in Fig. 12, have an immediate impact on the objective function due to the constraints it imposes. More specifically, a larger budget allows for better resource allocation and better working conditions overall, which in turn promotes greater equity in the working circumstances for drivers.

Additionally, we notice a noteworthy pattern in the mean freshness of the products that are delivered. Initially, as the budget increases, the freshness improves due to better logistics and more efficient handling processes. However, after reaching a certain point, the freshness begins to decline. The freshness eventually stabilizes and starts to rise again as the budget increases, suggesting that there is an ideal range where budget increases yield significant improvements in product quality.

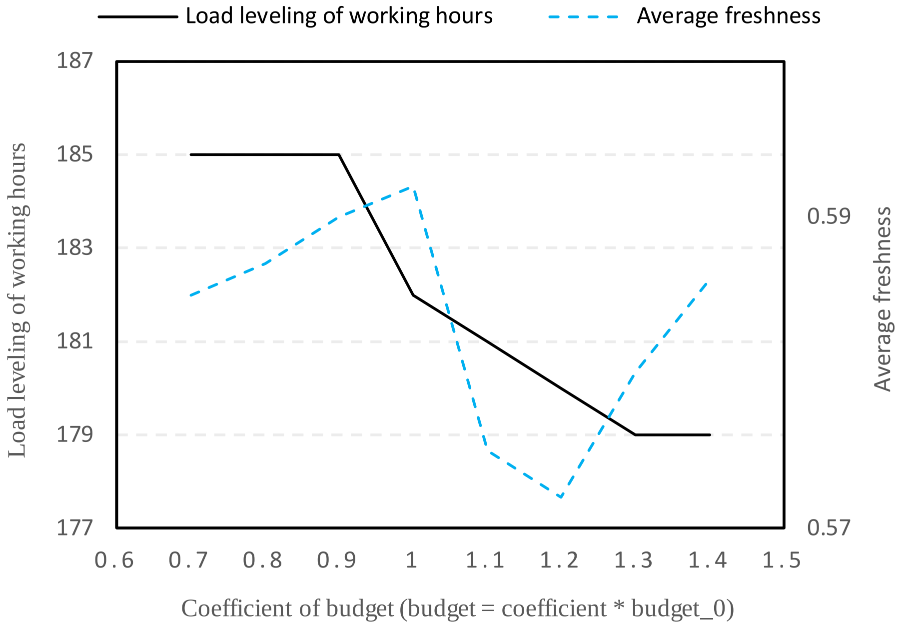

Fig. 12. The impact of budget changes on objective function

5. Conclusion

In order to reduce costs and delivery times, scheduling and routing for perishable goods is an important and practical problem. In this study, cross-dock is considered as a product distribution technique in the supply chain. Since sustainability is a relatively new concept in logistics systems, the model of scheduling and routing of vehicles in a sustainable cross-dock and its solution method were studied. Cross-dock scheduling is used to decide the sequence and allocation of incoming and outgoing vehicles in order to optimize cross-dock management goals. Therefore, in this research, literature in the field of sustainable vehicle routing was reviewed; then the new sustainable mixed integer model is presented. In the economic dimension of sustainability, there are various costs, including earliness and tardiness penalties, inventory holding and transportation costs. In the environmental dimension, the amount of fuel consumption and consequently the amount of carbon dioxide emissions is limited. In the social dimension, driver satisfaction is examined in order to balance drivers. Customer satisfaction is also considered due to the perishability of the products. We propose a GA based on fix-and-optimize solution in order to solve this model. To examine the efficiency of the proposed algorithm, 20 test problems are applied. In these test problems, the CPU time of using the pure mathematical model with the CPLEX solver is higher than the one of MGA algorithm. The case study of Tehran was also examined to show the efficiency of the model and is solved in two cases: 1) all decisions should be made in the GA algorithm and 2) CPLEX should optimize the decision related to the sequence of orders from customers. The results show that the second mode is efficient in the long run time. Also as a result of sensitivity analysis by decreasing the freshness life of the products, the objective function will be increased. The behavior of objective function with budget changes is similar to the behavior of the objective function with freshness life changes. In addition, based on the results, we can discuss about some managerial implications as follows:

- Integrating a sustainable mixed-integer model into cross-docking operations can significantly enhance decision-making in supply chain management by optimizing vehicle allocations and resource utilization, thereby reducing operational costs,
- Emphasizing sustainability enables managers to align economic, environmental, and social dimensions with corporate social responsibility objectives, enhancing brand reputation while ensuring regulatory compliance,
- the manger can make the working conditions of the drivers more equitable by giving up a small amount of profit,
- Incorporating driver satisfaction into scheduling enhances employee morale and retention, contributing to productivity,
- By strategizing routes to minimize fuel consumption and emissions, managers can effectively reduce environmental impacts,
- Optimizing order sequences for perishable goods improves customer satisfaction and fosters repeat business; and
- Adopting the GA-based algorithm enhances efficiency, particularly in complex logistics environments.

Insights from real-world applications, such as the case study in Tehran, underscore the model's practical relevance across different contexts, positioning organizations to better navigate logistical challenges and bolster supply chain resilience. This research can be developed in several ways: 1) using other methods such as recent metaheuristic algorithms to solve the proposed model and comparing the results with the results of the solution method of this study, 2) using other social considerations in the cross-dock operation, 3) solving the problem as a multi-objective problem.

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